The Common Factor of Bilateral U.S. Exchange Rates: What is it Related to?

Natalia Ponomareva and Jeffrey Sheen and Ben Wang

Macquarie University, Macquarie University, Macquarie University

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Natalia Ponomareva* Jeffrey Sheen† Ben Zhe Wang‡

Abstract

We identify a common factor driving a panel of fifteen monthly bilateral exchange rates against the U.S. dollar. We find this factor is closely related to U.S. nominal and real macroeconomic variables, financial market variables and commodity prices. Our results suggest this common factor is broadly related to the macroeconomic fundamentals in the Taylor rule and uncovered interest parity models. However, the set of fundamentals relevant to these models changes over time.

JEL Codes: C52, C53, F31, F47.

Key Words: Principal Component Analysis; Exchange Rate Models;

*Macquarie University, Australia; natalia.ponomareva@mq.edu.au.

†Macquarie University, Australia; jeffrey.sheen@mq.edu.au

‡Corresponding Author: E4A 432, Department of Economics, Macquarie University, Australia; ben.wang@mq.edu.au, [Tel:] +61298508500

1 Introduction

The movements of a bilateral exchange rate may be attributed to changing perceptions and events related to either or both currencies. By looking at a single bilateral rate, it can be difficult to disentangle these attributions. However if we consider a panel of bilateral exchange rates of one currency against several other currencies, it becomes possible to extract a common component responsible for the generalised movement of the chosen currency. It would then be of interest to see if this currency-specific component is related to domestic economic fundamentals for that currency.

The links between economic fundamentals and bilateral exchange rate fluctuations have been extensively explored in the economic literature (see **?** and Rossi (2013) for a comprehensive literature review). However, the results have been rather disappointing, especially in the case of exchange rate forecasting in the short-run (see the seminal paper by Meese and Rogoff (1983) and a more recent summary in Cheung, Chinn and Pascual (2005)). The reason is that each fundamental model is based on a particular set of economic variables guided by a particular macroeconomic theory, which may be overly restrictive when it comes to explaining and forecasting exchange rates in the short-run. Often these models use differentials of variables from the two countries, based on homogeneity assumptions. While this symmetry may be justified in theory, it may be too restrictive in practice.

Exchange rate modelling faces other problems. Many observed economic fundamentals used in exchange rate models are prone to measurement error, while unobservable fundamentals, such as risk premia, need indirect measures (Engel, Mark and West (2015)). Moreover, a fundamental model that works well for a particular period or currency may not necessary work well for other periods or currencies (Cheung et al. (2005)). This can imply that the measures of the economic variables used may not necessarily reflect the true driving force of exchange rates, and that different exchange rate theories may perform well in some time periods, and badly in others.

Recognizing these issues, this paper takes an atheoretical approach to investigating the link between macroeconomic variables and exchange rate dynamics. Using fifteen monthly growth rates of bilateral exchange rates against the U.S. dollar since 1999, we first extract common information contained in the panel of bilateral exchange rates using principal component analysis (PCA). We find that the most important factor (the first principal component) explains a half of the total variance across all bilateral exchange rates. Since this factor loads positively on all bilateral exchange rates, we call this factor the common factor. Given that the panel consists of the bilateral exchange rates with the U.S. dollar, a natural hypothesis is that this common factor is strongly related to U.S. macroeconomic conditions. We consider both nominal and real macroeconomic variables and financial market variables. Furthermore, since the U.S. is the world's leading economy and the U.S. dollar is the main invoicing currency for international trade and the vehicle currency for pricing commodities (Devereux, Shi and Xu (2010), Kamps (2006) and Goldberg and Tille (2008))[1], we also consider commodity prices. In addition to a full sample analysis, we investigate whether the link between the common factor and these economic fundamentals changes over time.

We find the main factor that drives the U.S. bilateral exchange rates is indeed related to the suggested economic fundamentals. In particular, we find that stock market volatility, lagged inflation, growth in capacity utilization and commodity prices (especially the gold price) are significantly linked to the common factor. In addition, our results suggest that the links between the common factor and these fundamentals do change over time.

[1] According to Kamps (2006) and Goldberg and Tille (2008), the shares of the U.S. dollar in exports and imports of European countries in the early 2000s are above 30%. These shares in Asian countries are 70–80%. In the U.S. more than 90% of exports and imports are invoiced in U.S. dollars.

One may argue that investigating a measure of the multilateral exchange rate may serve our purpose equally well. Commonly used measures of an effective exchange rate are calculated as weighted averages of bilateral exchange rates with currencies from major trading partners, with the weights depending on the relative importance of a trading partner. However, according to the Bank for International Settlements in their triennial survey of foreign exchange rate markets, trade in goods and services accounts for less than 0.5% of all foreign exchange transactions globally. This implies that a filter based on these trade weights should be largely irrelevant for estimating the common component of currency movements, particularly at higher frequencies. The common factor (i.e. the first principal component) extracted by the principal component analysis can be viewed as a filter that accounts for both capital shares as well as goods and services trade shares. Indeed, we show the common factor is more volatile than measures of the trade-weighted index (TWI), likely reflecting international capital flows responding to asset market conditions. Nevertheless, the common factor is highly correlated with measures of TWI, especially those including a broader range of trading partners.

Our paper builds on an evolving literature that explores the information content of a panel of bilateral exchange rates. For example, using 17 quarterly bilateral exchange rates against the U.S. dollar from 1973 to 2007, Engel et al. (2015) show a forecast strategy using the first three principal components can improve on the forecast of the random walk for the period 1999 to 2007. Wang and Wu (2015) demonstrate that the forecasts of bilateral exchange rates based on information extracted by the independent component analysis are also superior to the random walk. The improvement of forecasting performance is attributed to the fact that the independent principal component picks up information contained in the third moment of exchange rate changes. Unlike the aforementioned papers focusing on predictive performance of the information content, our paper investigates to which economic and financial variables the the common factor is related.

The rest of the paper is organised as follows. Section 2 identifies the common factor by using the Principal Component Analysis (PCA) and links it to U.S. economic variables and commodity prices. Section 3 discusses the relationship between this common factor and the economic variables over time. Section 4 concludes.

2 Estimating and identifying the common factor for U.S. bilateral exchange rates

Our aim in this section is to obtain the unobserved factors associated with the bilateral U.S. exchange rates. Our dataset contains the monthly standardized growth rates of nominal bilateral exchange rates of the U.S. dollar against fifteen currencies from Australia, Brazil, Canada, Denmark, Euro area, India, Japan, Mexico, New Zealand, Singapore, South Africa, South Korea, Taiwan, Thailand, and the United Kingdom for the period 1999.02–2015.02. We start in 1999 because it is the year when the euro was introduced. We consider monthly exchange rates calculated as monthly averages of daily exchange rates. The averaging allows smoothing of idiosyncratic movements of the daily exchange rates (due to the law of large numbers), and allows us to focus on systematic movements. All the bilateral exchange rates are defined as the units of foreign currency per U.S. dollar. Figure 1 plots their growth rates. Note the sharp appreciation of the U.S. dollar against most of the currencies during the crisis. This can be explained by the two accompanying facts: (i) the U.S. economy was considered a safe haven for financial investments even though the global financial crisis originated in the U.S., and (ii) the U.S. financial institutions were cautious about their balance sheet and withdrew their investments overseas.

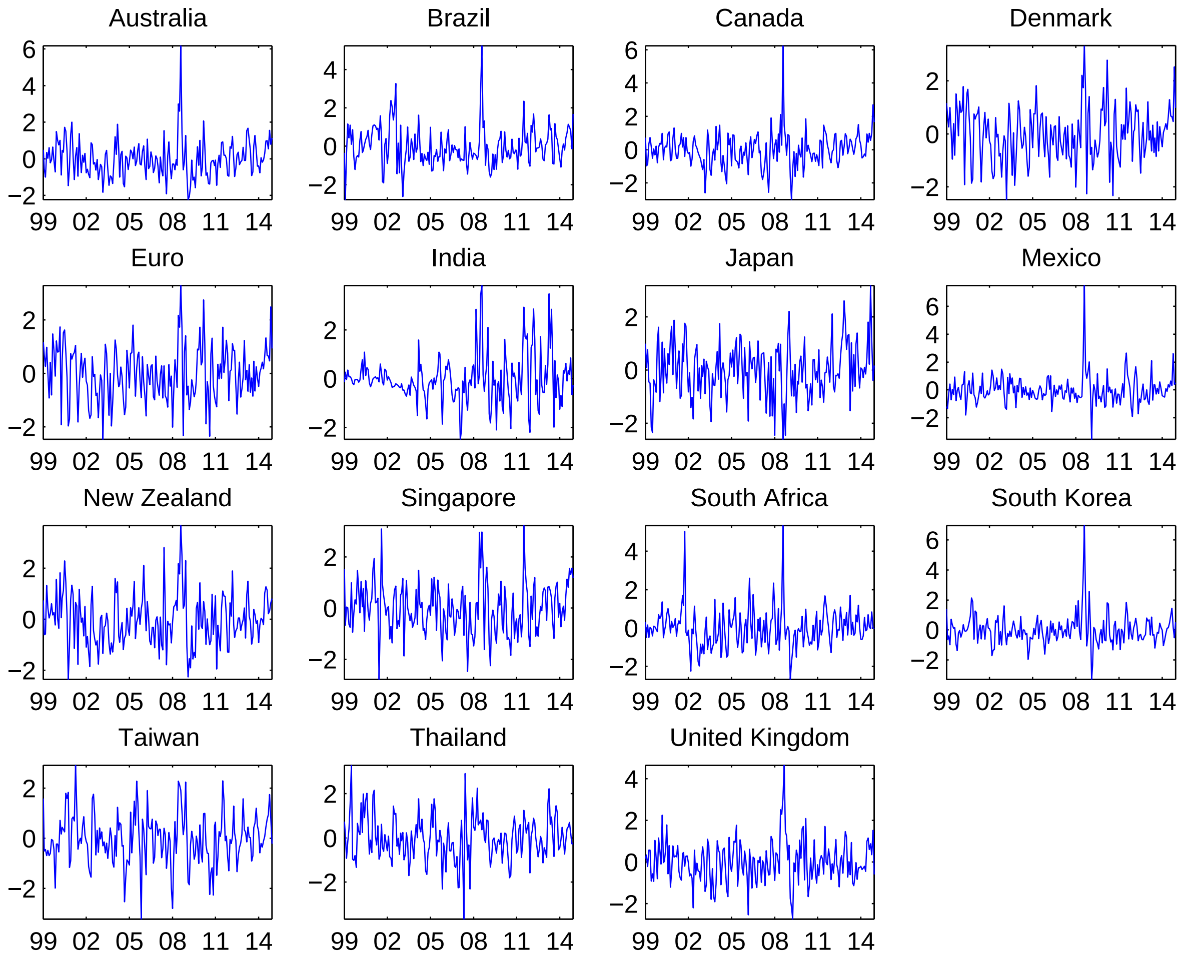

Figure 1: Growth rates of nominal exchange rates

Instead of examining individual bilateral exchange rates, we use cross sectional information to elicit the common factor that simultaneously drives all the bilateral exchange rates. Given the dominance of the U.S. economy, as well as the chosen bilateral design, it is natural to hypothesise that changes in U.S. fundamentals would cause significantly similar fluctuations in the fifteen bilateral exchange rates. If we can identify this common effect, it could have the following properties. First, it could simultaneously explain a significant proportion of the variances of the returns of bilateral exchange rates. Second, it could have statistical and economic significance in relation to U.S.

macroeconomic and financial variables. Third, it could have relatively unimportant relations with the other countries' variables. We consider these properties in turn.

2.1 Principal component analysis

We employ principal component analysis (PCA) to extract the common driving forces of our panel of fifteen (standardized) bilateral exchange rates. This yields fifteen orthogonal principal components. By comparing the scale of the eigenvalues of the variance-covariance matrix, we get an idea about the relative explanatory importance of the individual principal components. The top panel of Figure 2 shows a scree plot of the eigenvalues.

This scree plot indicates that the first principal component explains around a half of the total variance of the bilateral exchange rates returns and the first four components explain more than 74% of the total variance.[2] The bottom panel of Figure 2 shows the first principal component. Note the sharp appreciation of the U.S. dollar against most currencies during the financial crisis of 2008, which reflects the 'flight to safety' observed simultaneously for a majority of the bilateral exchange rates in the heat of the crisis.

Principal component analysis is often used to summarize the driving forces of a large panel of data with a few dominant factors. Principal components are constructed so that they are orthogonal and the first principal component has the largest variance (thus accounting for the most variability in the original panel), the second principal component has the second-largest variance and so on. However, since these principal components are statistical constructs, they do not always have an obvious economic interpretation. For instance, Engel et al. (2015) hypothesise the second principal com-

[2]The first four principal components explain 49.0%, 12.7%, 7.2% and 5.4% of the total variance respectively.

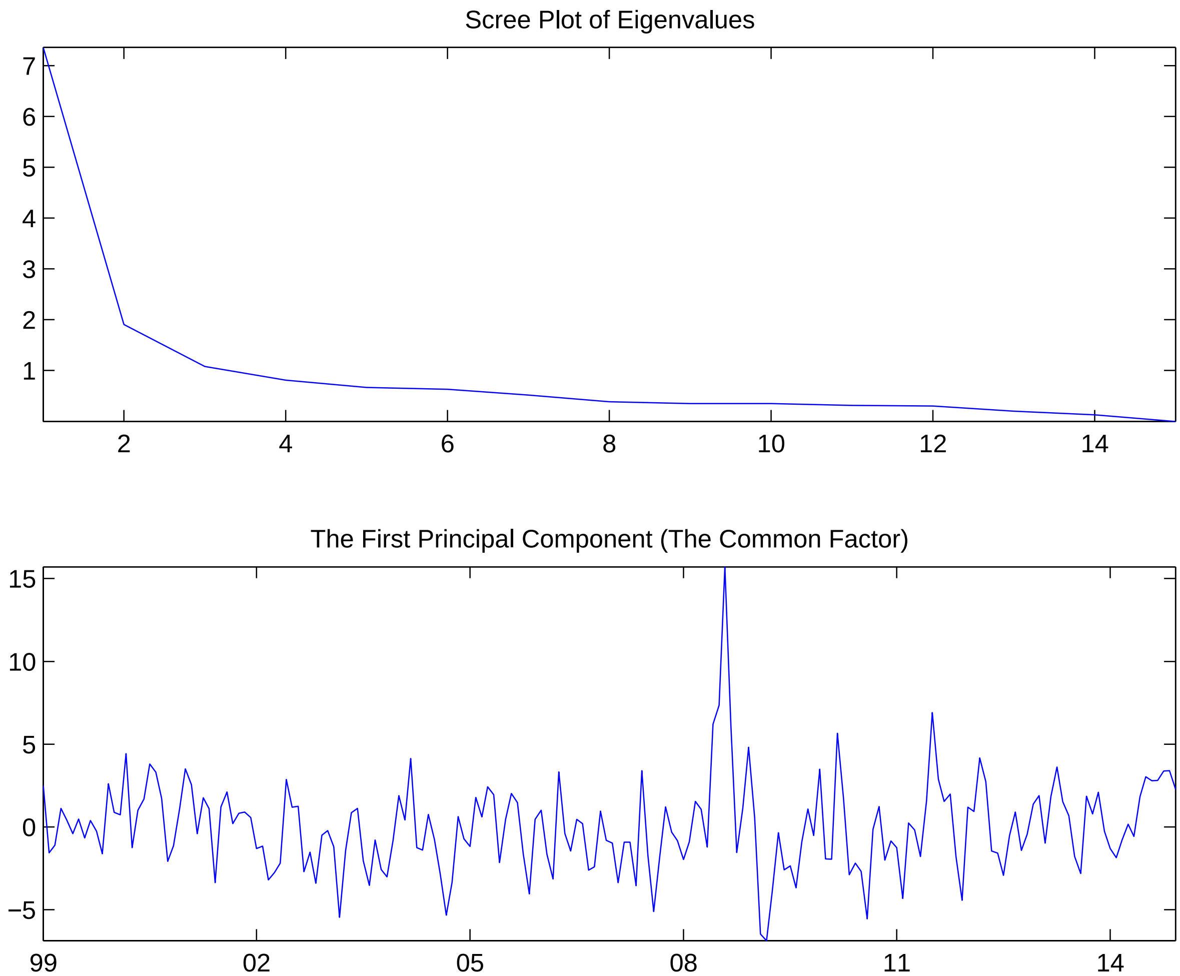

Figure 2: Scree plot of eigenvalues and the first principal component

ponent of their panel of exchange rates (expressed as the price of foreign currency in the U.S. dollars) is the German mark factor and Greenaway-McGrevy, Mark, Sul and Wu (2012) identify the first three factors to be euro/dollar, yen/dollar and Swiss frank/dollar in their panel of exchange rates.

We examine the correlation between the first four principal components and individual bilateral exchange rates in Table 1. The first column shows that the first principal component is strongly positively correlated with all bilateral exchange rates (apart from the Japanese yen with the smallest coorelation of 0.2) suggesting a common fac-

Table 1: Correlations with bilateral exchange rates

Country	PCA(1)	PCA(2)	PCA(3)	PCA(4)
Australia	0.88	0.11	-0.14	-0.01
Brazil	0.60	0.51	0.04	0.04
Canada	0.75	0.19	-0.18	-0.21
Denmark	0.79	-0.44	-0.32	0.03
Euro	0.78	-0.44	-0.32	0.04
India	0.66	0.34	0.24	0.21
Japan	0.20	-0.67	0.48	-0.28
Mexico	0.57	0.64	-0.04	-0.22
New Zealand	0.80	0.01	-0.21	0.16
Singapore	0.83	-0.24	0.20	-0.03
South Africa	0.65	0.14	0.08	-0.06
South Korea	0.76	0.21	0.26	-0.18
Taiwan	0.67	-0.13	0.42	-0.22
Thailand	0.56	-0.11	0.32	0.69
United Kingdom	0.72	-0.31	-0.30	-0.06

tor. The next three principal components are harder to interpret since the correlations do not provide such a clear-cut picture. The highest correlations of the second and the third principal components are with the Japanese yen, so these may be related to a Japan factor (which is plausible given a relatively low correlation of the first principal component with the yen/dollar bilateral exchange rate). The third and fourth principal components may also be related to some Asian factors given that the second-highest correlation of the PCA(3) is with the Taiwanese dollar/U.S. dollar exchange rate growth and the highest correlation of the PCA(4) is with the Thailand's baht/U.S. dollar exchange rate.

2.1.1 The common factor and multilateral exchange rates

Our focus of this paper is on the first principal component, since it is by far the largest single factor driving the bilateral exchange rates simultaneously. We refer to this principal component as the common factor of the U.S. bilateral exchange rates. Since the common factor is positively correlated with all bilateral exchange rates returns (Table 1), a rise in its value indicates an appreciation of the U.S. dollar.

One way to think about this common factor is that it is a measure of the monthly growth rate of the multilateral exchange rate, which is obtained using a statistical procedure without relying on explicit trade weights. It is natural to compare this measure to more widely used measures of multilateral exchange rates based on trade weights. Figure 3 plots the common factor against four alternative measures of the (growth rate of) multilateral exchange rates: broad and narrow indices constructed by the Bank of International Settlement (BIS)[3] and broad and major-currency trade-weighted indices (TWI) published by St. Louise Fed (FRED).

As can be seen from Figure 3, the common factor behaves similarly to the existing measures of multilateral exchange rates. The correlations ranges from 0.876 (FRED: Narrow) to 0.962 (FRED: Broad). The correlation is particular high for the measures containing a broader set of currencies (0.957 and 0.962). Despite the high correlations with these measures, our common factor exhibits higher variance, particularly at the height of the financial crisis in 2008. These patterns suggest that the common factor is closely linked to trade-weighted measures of multilateral exchange rates, and the difference may reflect the possible impact of differently-weighted financial flows on our common factor, particularly in volatile periods.

2.2 Covariates for the common factor

Although the common factor is a statistical construct, it ought to contain economic information. In this section we investigate possible links between economic fundamen-

[3]These are constructed as as geometric weighted averages of bilateral exchange rates.

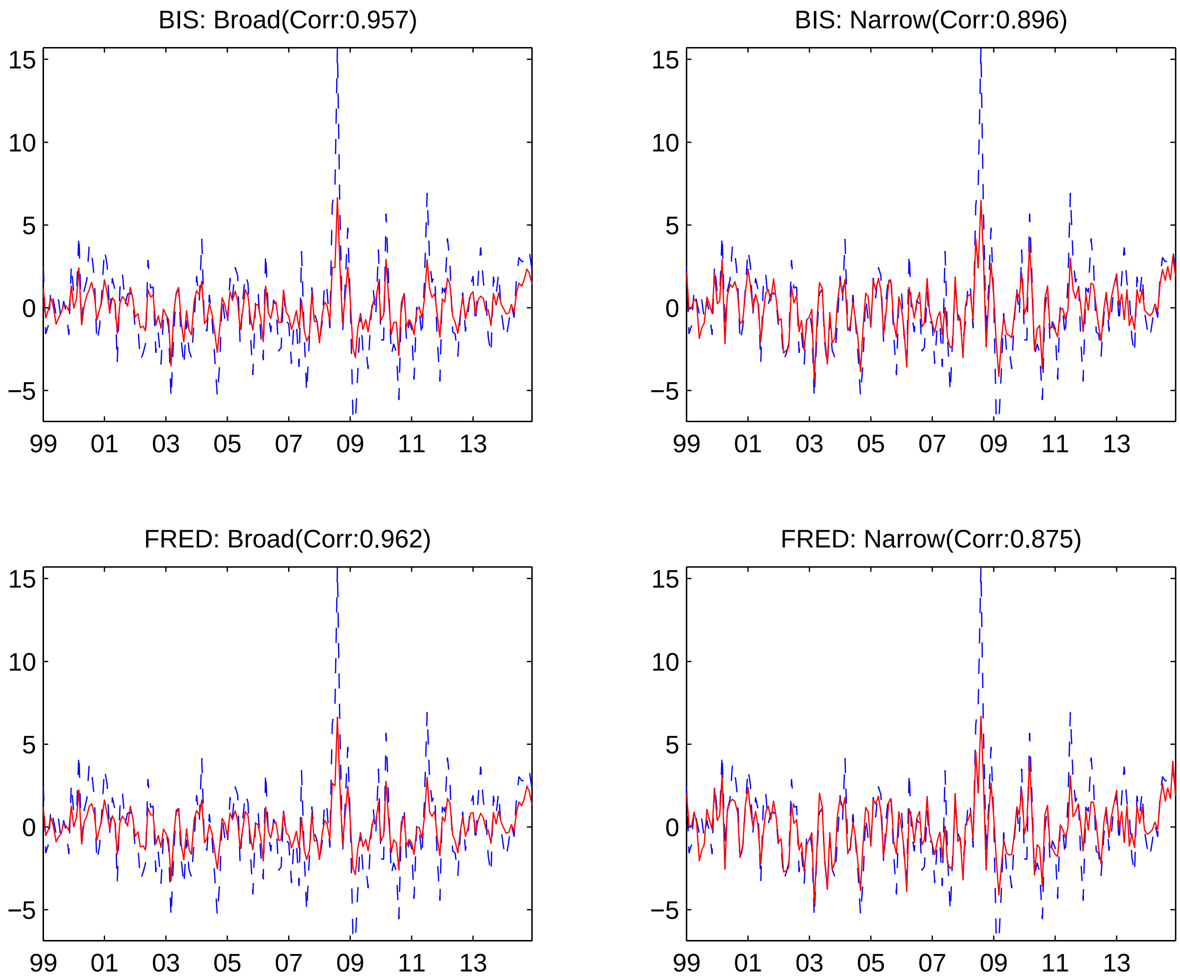

Figure 3: Comparison of the common factor with multilateral exchange rates. The common factor is shown as dashed blue.

tals and the common factor.

The fact that the common factor is positively correlated with all U.S. bilateral exchange rates leads us to hypothesise that it is related to U.S. macroeconomic and financial conditions. We are not restricted by any economic theory that demands a specific relationship between exchange rates and a particular set of economic fundamentals. Instead, we choose current and lagged fundamentals that are broadly consistent with several economic theories and rely on the data to elicit the set of fundamentals that provide the best fit for our common factor.

We select U.S. macroeconomic variables broadly based on both a typical Taylor rule model and the uncovered interest rate parity (UIP) model with a risk premium.

We consider the following variables related to Taylor rule models: current and expected inflation (CPI inflation and one year ahead consumer inflation expectation from the Michigan Survey of Consumers), measures of current and expected real activities including monthly growth of capital utilization, unemployment rate, growth of industrial production and a measure of leading indicator constructed by the Federal Reserve Bank of Philadelphia.

We choose the following variables related to UIP: various current and expected return measures including the federal funds rate, the yield slope (the difference between the ten-year government bond rate and three-month treasury bill rate), the monthly return on the S&P 500, and a measure of interest rate expectations (defined as a percentage of consumers expecting a decrease in the interest rate by the Michigan Survey of Consumers). It is known that the UIP model does not fit the data well unless it takes into account a risk premium. Therefore, we also consider various measures of risk and uncertainty including a smoothed recession probability measure (see Chauvet and Piger 2008), the consumer sentiment index from the Michigan survey of consumers, the monthly growth of the VIX index (known as the 'market fear index'), and the TED spread.

Since we hypothesise the common factor is primarily related to U.S. macroeconomic conditions, we consider the U.S. side of the theory in this section and later show the common factor is unrelated to the main Japanese and European macroeconomic variables.

There is an extensive theoretical and empirical literature on the co-movement of the U.S. dollar with commodity prices. Golub (1983) and Krugman (1983) develop theoretical models of the effects of oil price change on the exchange rate. Reboredo (2012) models oil price and exchange rate co-movements. Sari, Hammoudeh and Soytas (2010)[4], Sjaastad and Scacciavillani (1996), and Pukthuanthong and Roll (2011) explore the relationship between gold prices and currency values. To account for this link between commodity prices and the value of U.S. dollar we consider the growth rates of specific commodities such as crude oil and gold as well as more general commodity price measures, including the monthly growth of the commodity research bureau index, the London metal exchange index and the U.S. export weighted commodity price.

The data are obtained from the FRED database maintained by the Federal Reserve Bank of St. Louis and from Datastream. All variables, except for the recession probability, are standardized to have zero mean and unit standard deviation to assist in comparing their relative effects.

We estimate the following general AR(1) model:

$$p_t = c + \alpha p_{t-1} + X_t\beta' + X_{t-1}\gamma' + \epsilon_t, \tag{1}$$

where p_t is the common factor (the first principal component) obtained using the full sample, c is a constant and X_t is a vector of explanatory variables.

Model 1 considers all series in X_t and X_{t-1}. However, since many variables may provide correlated information about the underlying U.S. fundamentals that drive the

[4] Sari et al. (2010) examine the co-movements and information transmission among the gold price, oil price, and the US dollar/euro exchange rate and find evidence of a weak long-run equilibrium relationship but strong feedbacks in the short-run.

bilateral exchange rates, we need to shrink the set of explanatory variables. In Model 2 we shrink the set algorithmically by sequentially eliminating the most statistically insignificant variables until all variables are significant below the 5% level, while in Model 3, we employ a shrinkage technique to select the most relevant variables.

Table 2 shows the estimates and their associated statistical significance for all three models. Since we were unable to reject heteroskedasticity in the estimated residuals, we used White-robust standard errors. We rejected serial correlation and non-normality for the estimated residuals in all models. The fit of Model 1, which includes all U.S. variables and commodity prices as regressors, is good with an adjusted R^2 of 0.39. For Model 2, which selects algorithmically only statistically significant variables, the adjusted R^2 is slightly higher at 0.43. Focusing on Model 2, the key parameter estimates indicate that the following play an important role in driving the common factor: growth rates of the SP500 (and its lag), the VIX, the gold price and U.S. weighted commodity price as well as lagged inflation, growth of capacity utilization, the yield slope, interest rate expectations, and the lagged common factor itself.

As a test of our shrinkage choices in Model 2, we elicit the most important of our U.S. variables that co-vary with the common factor by running a Lasso regression. This is a statistical shrinkage and selection method for linear regression that penalizes the absolute value of estimated coefficients (see Tibshirani 1996).[5] We choose the penalty level by running cross-validations that maximize the predictive power of the model.[6] The results are shown in the last column of Table 2 as Model 3. The growth of the

[5] This is done by minimizing the sum of squared errors subject to a bound on the sum of the absolute values of the coefficients. The larger the penalty, the smaller the set of selected explanatory variables. This provides a useful variable selection method, particularly in the presence of multicollinearity.

[6] We use a ten-fold cross-validation at each value of the penalty weighting. For each cross-validation, the data is randomly partitioned into ten slots, and the model is estimated using one slot and fitted into the other nine. The mean squared error is calculated from this fitting process, and the optimal weight is chosen to minimize the mean squared error. Since this cross-validation process is embedded in a random process, we conduct ten Monte Carlo simulations for each cross-validation, selecting the optimal set of variables based on the Monte Carlo integration of the ten simulations.

Table 2: OLS results

Variable	Model 1	Model 2	Model 3
constant	-0.08	–	–
Inflation$_t$	0.32	–	–
Inflation expecation$_t$	0.23	–	–
Growth of capacity utilization$_t$	-0.47	–	–
Unemployment rate$_t$	-1.14	–	–
Growth of industrial production$_t$	3.17**	–	–
Leading indicator$_t$	0.26	–	–
Federal fund rate$_t$	-2.09	–	–
Yield slope$_t$	-1.28	–	–
Growth of SP500$_t$	0.66**	0.69***	–
Interest rate expectation: lower$_t$	-0.13	–	–
Recession probability$_t$	-4.30	–	–
Consumer sentiment$_t$	-0.33	–	–
Growth of VIX$_t$	0.80**	0.79***	0.39**
Ted spread$_t$	-0.14	–	–
Growth of crude oil price$_t$	-0.19	–	–
Growth of gold price$_t$	-0.73***	-0.69***	-0.69***
Growth of commodity research beaural index$_t$	-0.26	–	–
Growth of London metal exchange index$_t$	0.36	–	–
Growth of U.S export weighted commodity price$_t$	-0.47*	-0.55***	-0.48**
Inflation$_{t-1}$	0.42	0.77***	0.56***
Inflation expectation$_{t-1}$	0.13	–	–
Growth of capacity utilization$_{t-1}$	-0.60**	-0.65***	-0.45***
Unemployment rate$_{t-1}$	1.32	–	–
Growth of industrial production$_{t-1}$	-2.82**	–	–
Leading indicator$_{t-1}$	-0.65	–	–
Federal fund rate$_{t-1}$	2.07	–	–
Yield slope$_{t-1}$	1.67*	0.49***	–
Growth of SP500$_{t-1}$	0.43	0.46***	–
Interest rate expectation: lower$_{t-1}$	0.55***	0.45***	–
Recession probability$_{t-1}$	4.87	–	–
Consumer sentiment$_{t-1}$	0.65	–	–
Growth of VIX$_{t-1}$	-0.00	–	–
Ted spread$_{t-1}$	0.02	–	–
Growth of crude oil price$_{t-1}$	-0.26	–	–
Growth of gold price$_{t-1}$	0.01	–	–
Growth of commodity research bureau index$_{t-1}$	0.10	–	–
Growth of London metal exchange index$_{t-1}$	-0.08	–	–
Growth of U.S export weighted commodity price$_{t-1}$	0.01	–	–
p$_{t-1}$	0.23**	0.23***	0.15**
Adjusted R^2:	0.39	0.43	0.37
Significance:	***: 1%	**: 5%	*: 10%

gold price, the VIX and the U.S. weighted commodity price as well as lagged inflation, growth of capacity utilization, and the common factor itself are significant in this model. The results suggest that while the common factor may not fully conform with any particular theoretical model, it is broadly linked to the UIP model, the Taylor rule model and commodity prices. This parsimonious selection of variables explains 37% of the variance of the common factor.

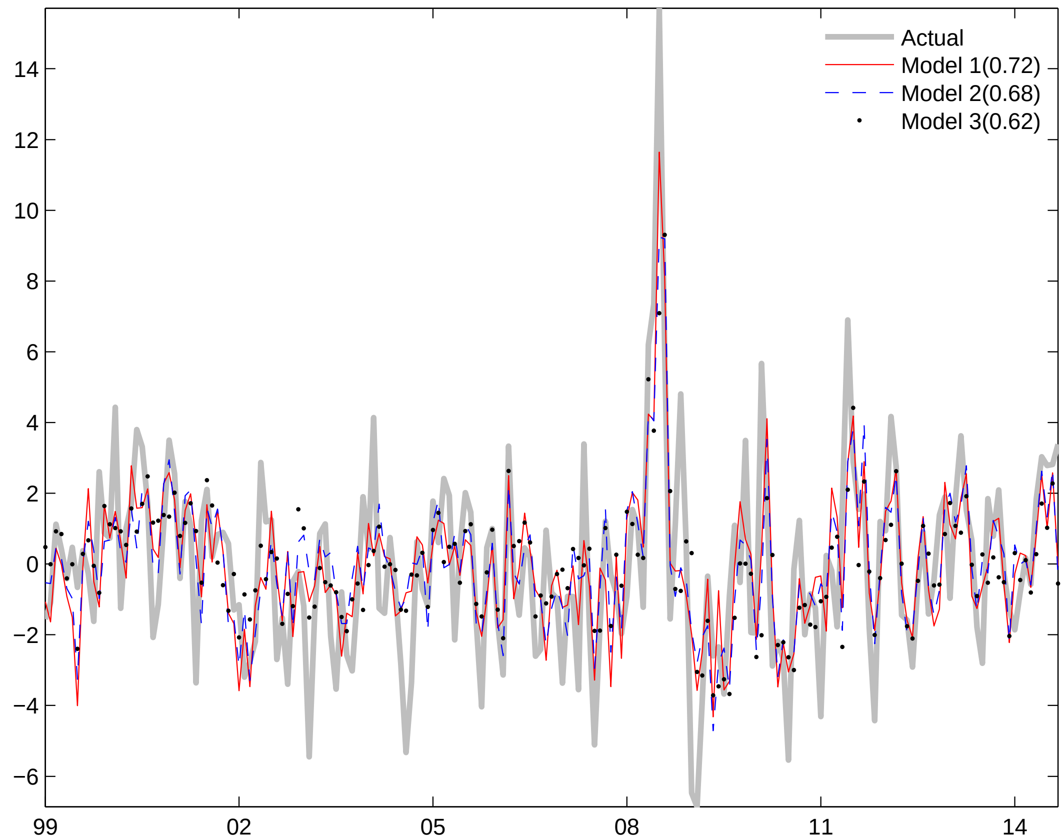

Figure 4: Actual and fitted values of the common factor. The correlation between the two are shown in brackets for each model.

Figure 4 shows actual and fitted values of the common factor for the three models. All fitted series appear to match the sharp changes in the common factor. The correlation between the fitted and actual values of the common factor are 0.72, 0.68 and 0.62 respectively for the three models considered. The 2008 spike is mostly well picked, as are the lesser turning points. Overall, the results demonstrate that the common factor is reasonably well represented by the U.S. variables and commodity prices.[7]

[7]When commodity prices are excluded from the set of variables the correlations are 0.63, 0.56

2.3 The contributions of other countries to the common factor

We have hypothesised that the common factor is related to domestic U.S. fundamentals and commodity prices. However, it is possible that other major economies may play some role in driving the common factor of the U.S. bilateral exchange rates (i.e. third country effects may be present as in Mark and Berg (2013)). Therefore, we test this hypothesis by regressing the error term of Equation (1) on the current and lagged inflation, unemployment rate and a consumer confidence measure for Japan and the Euro area. None of the explanatory variable is significant and the likelihood ratio test against the model with only a constant has a p-value of 0.92, indicating these additional variables do not explain the error term of Equation (1).

2.4 Causality

Although the main focus of this paper is on extracting the information content of the common factor, it would be interesting to investigate the causal relationship (in the Granger sense) between the common factor and the Lasso selected variables (from Model 3). Accordingly we estimate a classical VAR with variables selected by Lasso in Model 3: U.S export weighted commodity price, capacity utilization, inflation, growth of VIX, gold price and the common factor. The lag order is set to 1 according to the Schwarz information criterion. Variance decomposition in Table 3[8] demonstrates that the common factor is largely driven by its own lag and growth of the U.S export weighted commodity price in both the short- and long-run. Inflation plays no role in the short-run but explains about 8% in the long-run. The results are robust to the

and 0.53 respectively for the three models. These numbers are still quite high and together with the fact that the Lasso chooses the similar set of the U.S. fundamentals in the cases with or without commodity prices in the variable set, this demonstrates that the results on the relationship between the U.S. fundamentals and the common factor are quite robust. The results for the dataset without commodity prices are available on request.

[8]The full estimation results are available on request.

ordering of the variables. Growth of the gold price explains 6%-7% of the variance of the common factor, but this result is not robust to a change of the variables ordering. In order to fully understand the causality between gold and the common factor a more sophisticated structural model is required, which lies beyond the scope of this paper.

Table 3: Variance decomposition of the common factor

	1 Month	3-Month	6-Month	12-Month	24-Month
Growth of U.S export weighted commodity price	10.60	9.33	9.90	12.00	12.63
Growth of capacity utilization	0.03	2.24	2.24	2.12	2.10
Inflation	0.04	1.70	4.84	7.36	7.91
Growth of VIX	1.63	2.44	2.33	2.19	2.15
Growth of gold price	6.96	6.54	6.29	6.03	5.98
The lagged common factor	80.73	77.76	74.39	70.29	69.23

3 The common factor and fundamental variables across time

Having found a significant statistical relationship between the common factor and a parsimonious set of U.S. economic fundamentals and commodity prices for the full sample, we now explore how this relationship evolves over time. We conduct expanding window Lasso regressions as in equation (1). In each regression we firstly construct the common factor using the PCA and then use Lasso regression for variable selection.

3.1 Expanding window regressions

The results for the expanding window regressions are presented in Figure 5, and the estimation runs from 2003.4 until the end of the sample in 2015.02. The final regression results coincide with what we presented in Model 3 of Table 2. The highlighted area indicates the NBER recession period.

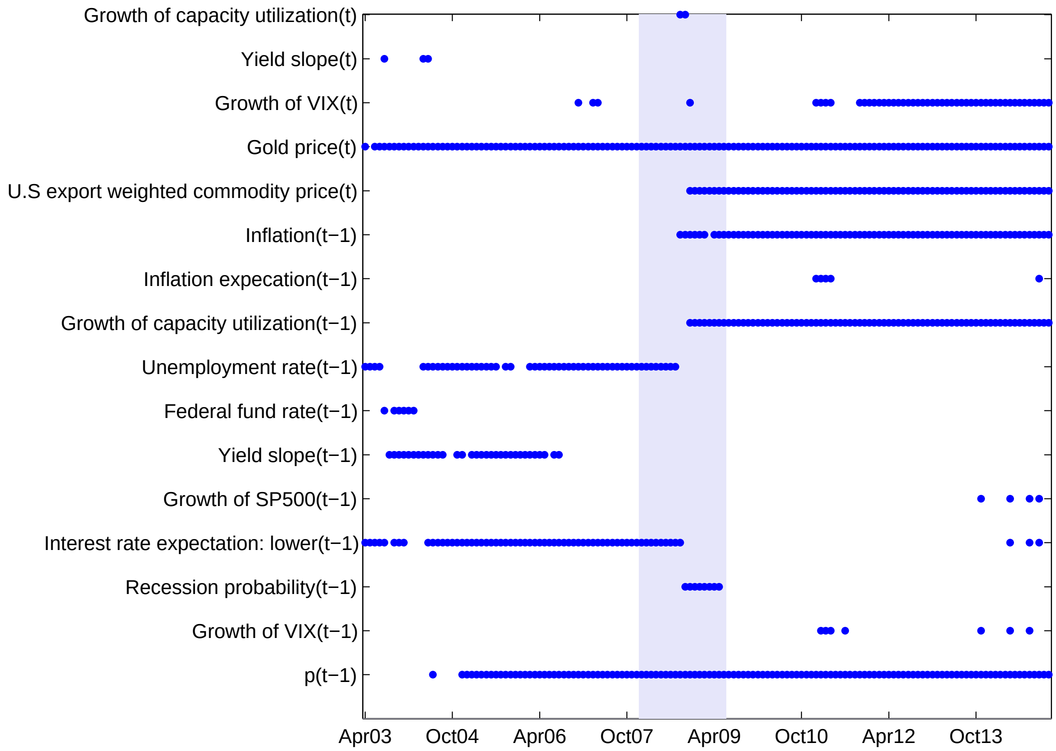

Figure 5: U.S. variables selected by the Lasso across time in expanding window regressions. Only variables significant at some stage are presented in the graph.

The pattern of selected variables suggests that the links between the current common factor and its lagged value as well as the current growth of gold price are relatively stable over time. The results also indicate a change in the set of macroeconomic fundamentals best linked to the common factor. In the period leading up to the 2008 crisis, the lagged unemployment rate, FED rate, yield slope and interest rate expectations appear to be important. During the crisis, the lagged recession probability started to play a role for a short time. In addition, during and after the crisis the current growth of VIX, the U.S. export weighted commodity price, lagged inflation and growth of capacity utilization became significant.

Our results suggest that both the typical Taylor rule and UIP models are relevant for bilateral panel exchange rate determination. However, the macroeconomic fundamentals broadly consistent with these theories seem to evolve over time. For instance, the measure of economic activity switches from the unemployment rate to growth of capacity utilization after the 2008 crisis. Inflation, while not playing any role in the pre-crisis period, appears to be important after the crisis. This may indicate that the financial market participants used to monitor the labour market closely in anticipation of policy rate decisions, but switched to monitoring inflation and capacity growth once the policy rate hit the zero lower bound. We also find the common factor is linked to expected interest rates (via the yield slope and the survey measure of interest rate expectations) in the pre-crisis period but the link vanishes in the post-crisis period. Instead, a measure of risk (growth of VIX) becomes important, indicating that the risk component dominates the yield component as the interest rate hits the zero lower bound. Our results highlight the the fact that a mixture of fundamental models and measurements can potentially do well in fitting (and forecasting as in Wright (2008)) exchange rate dynamics.

4 Conclusion

Using a panel of fifteen bilateral exchange rates with the U.S. dollar, this paper identifies a common factor that explains around a half of the cross-sectional variance in the exchange rates returns. Our derived common factor is highly correlated with the various measures of trade-weighted indices. The advantage of this new measure would be that it does not rely on trade weights exclusively and as such, implicitly takes into account trade in financial assets. This is crucial in a situation when the majority of exchange rate transactions involve trades in financial instruments. Financial trade-weights are not generally available, but are obviously highly important especially in volatile times.

We find that the common factor is related to U.S. economic fundamentals and commodity prices. In particular it is linked to the growth of the VIX index, inflation and capacity utilization, as well as the gold price and the U.S. export weighted commodity index. We show that the behaviour of the common factor is generally consistent with both the Taylor rule and uncovered interest rate models, but the variables relevant to these theories differ in their contributions before, during and after the 2008 crisis. Our results indicate a mixture of theories and measurements is important in order to obtain a best fit for exchange rates.

The benchmark for comparing structural exchange rate models ought to be ramped up to involve bilateral panels. Will bilateral panels be more informative for other large or small countries, for developing and developed ones, and for commodity-exporting and -importing ones? We leave this question to future research.

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